Constraint Satisfaction Problems

Chapter 6

Outline

◇ CSP definition

◇ Backtracking search for CSPs

◇ Constraint propagation

◇ Problem structure and problem decomposition

◇ Local search for CSPs

◇ Assignment 2

Acknowledgements:

slides are based partly on Krzysztof Kuchciński's lecture notes

original AIMA slides are modified by Jacek Malec for the EDA132 course

Constraint satisfaction problems (CSPs)

Standard search problem:
state is a "black box"—any old data structure
that supports goal test, eval, successor

CSP:
state is defined by variables X_i with values from domain D_i

goal test is a set of constraints specifying
allowable combinations of values for subsets of variables

Simple example of a **formal representation language**

Allows useful **general-purpose** algorithms with more power than standard search algorithms

CSP definition

A **Constraint Satisfaction Problem** consists of three components: X, D and C:
X is a set of variables, $\{X_1, \ldots, X_n\}$,
D is a set of domains, $\{D_1, \ldots, D_n\}$, one for each variable,
C is a set of constraints that specify allowable combinations of values.
Each constraint C_i consists of a pair $<scope, rel>$.

A **solution** to a CSP is a consistent, complete assignment.

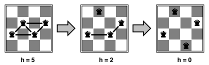
Example: 4-Queens as a CSP

Assume one queen in each column. Which row does each one go in?

Variables Q_1, Q_2, Q_3, Q_4

Domains $D_i = \{1, 2, 3, 4\}$

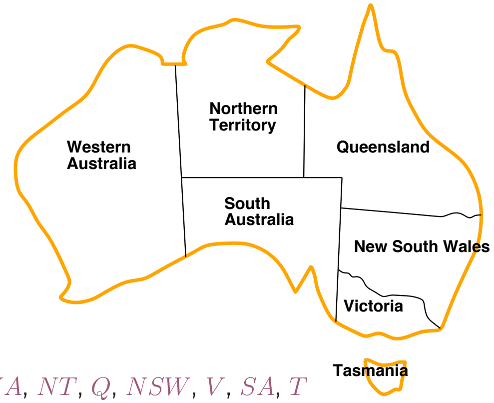
Constraints
$Q_i \neq Q_j$ (cannot be in same row)
$|Q_i - Q_j| \neq |i - j|$ (or same diagonal)



Translate each constraint into set of allowable values for its variables

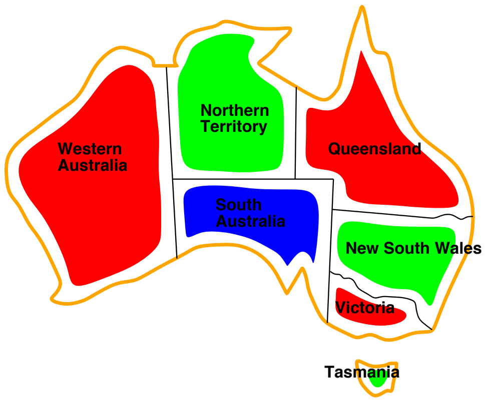
E.g., values for (Q_1, Q_2) are $(1,3)$ $(1,4)$ $(2,4)$ $(3,1)$ $(4,1)$ $(4,2)$

Example: Map-Coloring



Variables WA, NT, Q, NSW, V, SA, T
Domains $D_i = \{red, green, blue\}$
Constraints: adjacent regions must have different colors
e.g., $WA \neq NT$ (if the language allows this), or
$(WA, NT) \in \{(red, green), (red, blue), (green, red), (green, blue), \ldots\}$

Example: Map-Coloring contd.

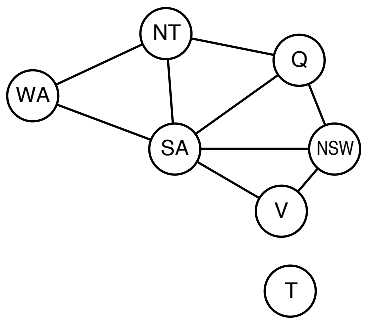


Solutions are assignments satisfying all constraints, e.g.,
$\{WA = red, NT = green, Q = red, NSW = green, V = red, SA = blue, T = green\}$

Constraint graph

Binary CSP: each constraint relates at most two variables

Constraint graph: nodes are variables, arcs show constraints



General-purpose CSP algorithms use the graph structure
to speed up search. E.g., Tasmania is an independent subproblem!

Varieties of CSPs

Discrete variables

- finite domains; size $d \Rightarrow O(d^n)$ complete assignments
  - ♢ e.g., Boolean CSPs, incl. Boolean satisfiability (NP-complete)
- infinite domains (integers, strings, etc.)
  - ♢ e.g., job scheduling, variables are start/end days for each job
  - ♢ need a constraint language, e.g., $StartJob_1 + 5 \leq StartJob_3$
  - ♢ linear constraints solvable, nonlinear undecidable

Continuous variables

- ♢ e.g., start/end times for Hubble Telescope observations
- ♢ linear constraints solvable in poly time by LP methods

Varieties of constraints

Unary constraints involve a single variable,
e.g., $SA \neq green$

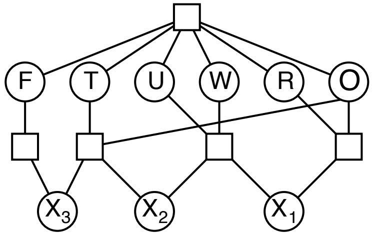
Binary constraints involve pairs of variables,
e.g., $SA \neq WA$

Higher-order constraints involve 3 or more variables,
e.g., cryptarithmetic column constraints,
sometimes called (misleadingly) global constraints

Preferences (soft constraints), e.g., red is better than $green$
often representable by a cost for each variable assignment
→ constrained optimization problems

Example: Cryptarithmetic

```
   T W O
 + T W O
 -------
 F O U R
```



Variables: $F\ T\ U\ W\ R\ O\ X_1\ X_2\ X_3$
Domains: $\{0,1,2,3,4,5,6,7,8,9\}$
Constraints
alldiff(F,T,U,W,R,O)
$O + O = R + 10 \cdot X_1$, etc.

Real-world CSPs

Assignment problems
e.g., who teaches what class

Timetabling problems
e.g., which class is offered when and where?

Hardware configuration

Spreadsheets

Transportation scheduling

Factory scheduling

Floor-planning

Notice that many real-world problems involve real-valued variables

Standard search formulation (incremental)

Let's start with the straightforward, dumb approach, then fix it

States are defined by the values assigned so far

♢ Initial state: the empty assignment, $\{\,\}$

♢ Successor function: assign a value to an unassigned variable
that does not conflict with current assignment.
⇒ fail if no legal assignments (not fixable!)

♢ Goal test: the current assignment is complete

1) This is the same for all CSPs!
2) Every solution appears at depth n with n variables
⇒ use depth-first search
3) Path is irrelevant, so can also use complete-state formulation
4) $b = (n - \ell)d$ at depth ℓ, hence $n!d^n$ leaves!!!!

Backtracking search

Variable assignments are commutative, i.e.,
$[WA = red$ then $NT = green]$ same as $[NT = green$ then $WA = red]$

Only need to consider assignments to a single variable at each node
⇒ $b = d$ and there are d^n leaves

Depth-first search for CSPs with single-variable assignments
is called backtracking search

Backtracking search is the basic uninformed algorithm for CSPs

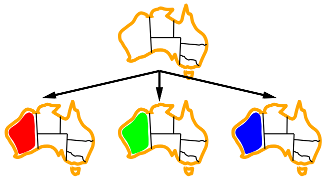
Can solve n-queens for $n \approx 25$

Backtracking search

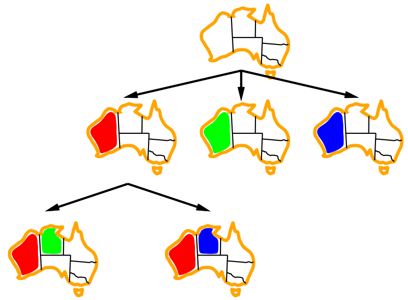
```
function Backtracking-Search(csp) returns solution/failure
   return Backtrack({ }, csp)

function Backtrack(assignment, csp) returns solution/failure
   if assignment is complete then return assignment
   var ← Select-Unassigned-Variable(Variables[csp], assignment, csp)
   for each value in Order-Domain-Values(var, assignment, csp) do
       if value is consistent with assignment given Constraints[csp] then
           add {var = value} to assignment
           result ← Backtrack(assignment, csp)
           if result ≠ failure then return result
           remove {var = value} from assignment
   return failure
```


Backtracking example

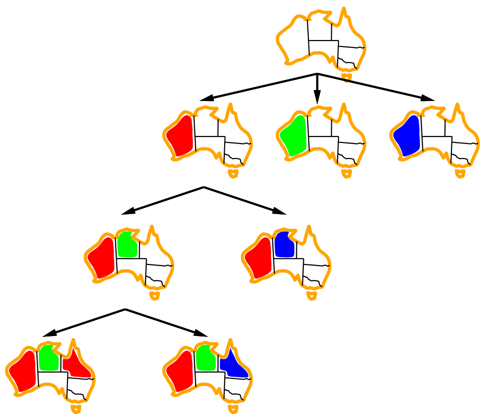
Backtracking example



Backtracking example



Backtracking example



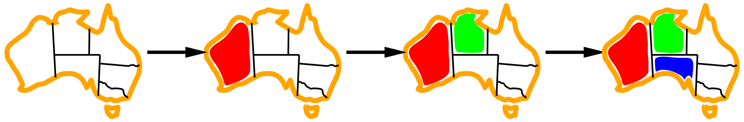
Improving backtracking efficiency

General-purpose methods can give huge gains in speed:

1. Which variable should be assigned next?
2. In what order should its values be tried?
3. Can we detect inevitable failure early?
4. Can we take advantage of problem structure?

Minimum remaining values

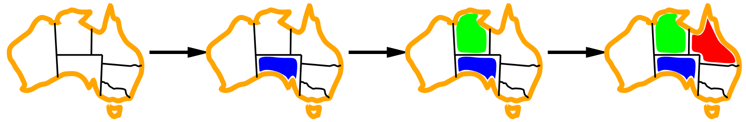
Minimum remaining values (MRV):
choose the variable with the fewest legal values



Degree heuristic

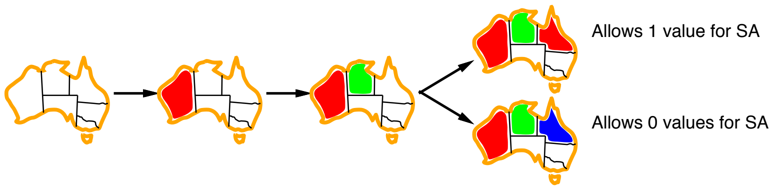
Tie-breaker among MRV variables

Degree heuristic:
choose the variable with the most constraints on remaining variables



Least constraining value

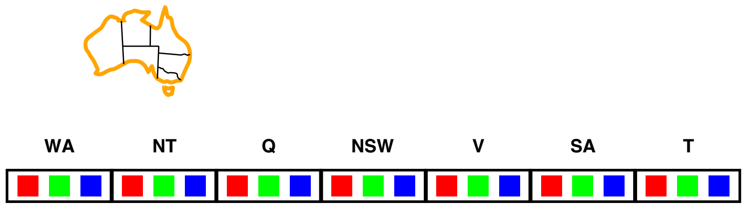
Given a variable, choose the least constraining value:
the one that rules out the fewest values in the remaining variables



Combining these heuristics makes 1000 queens feasible

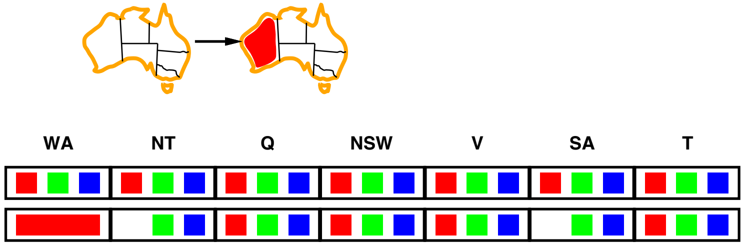
Forward checking

Idea: Keep track of remaining legal values for unassigned variables
Terminate search when any variable has no legal values



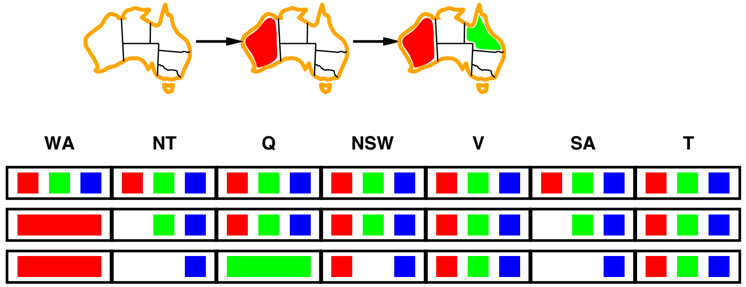
Forward checking

Idea: Keep track of remaining legal values for unassigned variables
Terminate search when any variable has no legal values



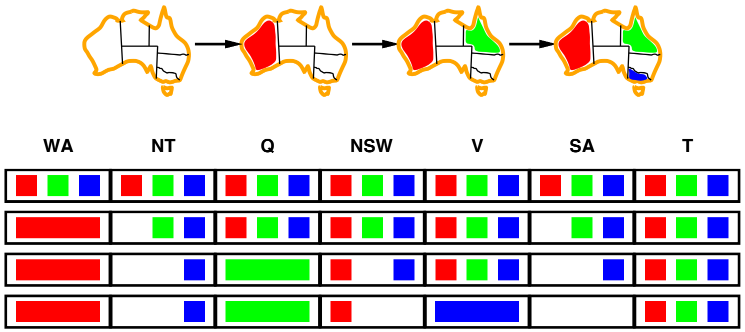
Forward checking

Idea: Keep track of remaining legal values for unassigned variables
Terminate search when any variable has no legal values



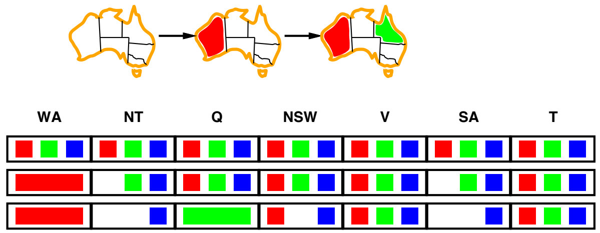
Forward checking

Idea: Keep track of remaining legal values for unassigned variables
Terminate search when any variable has no legal values



Constraint propagation

Forward checking propagates information from assigned to unassigned variables, but doesn't provide early detection for all failures:



NT and SA cannot both be blue!

Constraint propagation repeatedly enforces constraints locally

Node consistency

Simplest form of propagation: makes each node node-consistent

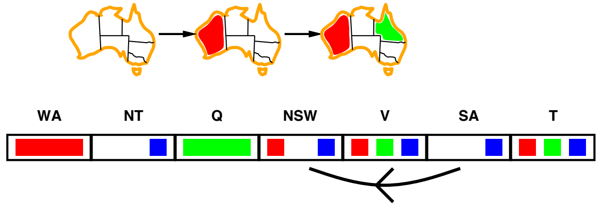
Node X is node-consistent iff
for **every** value x of X all the unary constraints of X are satisfied

Needs to be run only once.

Arc consistency

This form of propagation makes each arc consistent

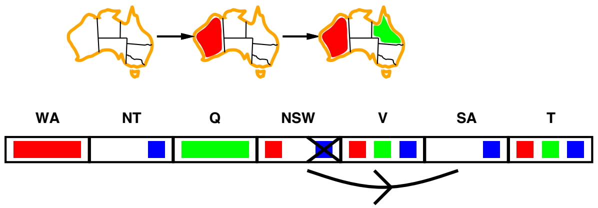
$X \rightarrow Y$ is consistent iff
for **every** value x of X there is **some** allowed y



Arc consistency

This form of propagation makes each arc consistent

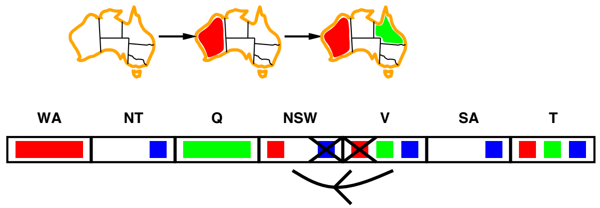
$X \rightarrow Y$ is consistent iff
for **every** value x of X there is **some** allowed y



Arc consistency

This form of propagation makes each arc consistent

$X \rightarrow Y$ is consistent iff
for **every** value x of X there is **some** allowed y

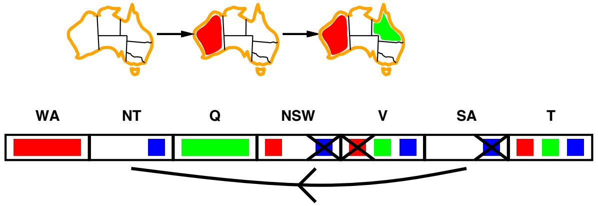


If X loses a value, neighbors of X need to be rechecked

Arc consistency

This form of propagation makes each arc consistent

$X \to Y$ is consistent iff
  for **every** value x of X there is **some** allowed y



If X loses a value, neighbors of X need to be rechecked

Arc consistency detects failure earlier than forward checking

Can be run as a preprocessor or after each assignment

Arc consistency algorithm

function AC-3(*csp*) **returns** the CSP, possibly with reduced domains
  inputs: *csp*, a binary CSP with variables $\{X_1, X_2, \ldots, X_n\}$
  local variables: *queue*, a queue of arcs, initially all the arcs in *csp*

  while *queue* is not empty **do**
    $(X_i, X_j) \leftarrow$ REMOVE-FIRST(*queue*)
    if REMOVE-INCONSISTENT-VALUES(X_i, X_j) **then**
      for each X_k **in** NEIGHBORS[X_i] **do**
        add (X_k, X_i) to *queue*

---

function REMOVE-INCONSISTENT-VALUES(X_i, X_j) **returns** true iff succeeds
  removed ← *false*
  for each x **in** DOMAIN[X_i] **do**
    if no value y in DOMAIN[X_j] allows (x,y) to satisfy the constraint $X_i \leftrightarrow X_j$
      then delete x from DOMAIN[X_i]; *removed* ← *true*
  return *removed*

$O(n^2d^3)$, can be reduced to $O(n^2d^2)$ (but detecting **all** is NP-hard)

Path consistency

Imagine coloring Australia, but only with two colors.

Arc consistency is not helpful in detecting problems, as every variable already is arc consistent.

A two-variable set $\{X_i, X_j\}$ is path-consistent with a third variable X_m if,
  for **every** assignment $\{X_i = a, X_j = b\}$
  consistent with the constraints on $\{X_i, X_j\}$,
  there is an assignment to X_m
  that satisfies the constraints on $\{X_i, X_m\}$ and $\{X_m, X_j\}$.

Example: consider $\{WA, SA\}$ path consistent wrt NT (in 2-coloring).

Path consistency checking algorithm PA-2, by Mackworth, resembles AC-3.

k-consistency is a generalization of arc and path consistency.

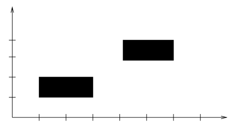
Global constraints

Involve an arbitrary number of variables, but not necessarily all.

◊ alldiff

◊ atmost, e.g. $atmost(10, X_1, X_2, X_3, X_4)$

◊ diff2, e.g. $diff2([[x_1, y_1, dx_1, dy_1], [x_2, y_2, dx_2, dy_2]], \ldots)$



◊ cumulative (scheduling),

◊ bounds propagation and bounds consistency
  Instead of $\{v_1, v_2, , \ldots, v_n\}$ we deal with $[v_1..v_n]$.

Backtracking search with inference

```
function Backtracking-Search(csp) returns solution/failure
   return Backtrack({ }, csp)

function Backtrack(assignment, csp) returns solution/failure
   if assignment is complete then return assignment
   var ← Select-Unassigned-Variable(Variables[csp], assignment, csp)
   for each value in Order-Domain-Values(var, assignment, csp) do
       if value is consistent with assignment given Constraints[csp] then
           add {var = value} to assignment
           inferences ← Inference(csp, var, value)
           if inferences ≠ failure then
              add inferences to assignment
              result ← Backtrack(assignment, csp)
              if result ≠ failure then return result
           remove {var = value} from assignment
   return failure
```


Sudoku

Constraints programming has finally reached the masses,
thousands of newspaper readers are solving their daily constraint problem
(Helmut Simonis, Imperial College)

2	6		3					
5						7		
					1		4	
6			5			2		
		4			8			1
	5		9					
		7						3
					4		1	6

Sudoku

Variables: `v[i,j] :: {1..9}`

2	6		3					
5						7		
					1		4	
6			5			2		
		4			8			1
	5		9					
		7						3
					4		1	6

Sudoku

Variables: `v[i,j] :: {1..9}`
Constraints:

```
// Rows
v[1,1] != v[1,2],...
// Columns
v[1,1] != v[2,1],...
// Squares
v[1,1] != v[2,2],...
```

2	6		3					
5						7		
					1		4	
6			5			2		
		4			8			1
	5		9					
		7						3
					4		1	6

Sudoku

First row, simple consistency check:

2
6
{1, 8..9}
3
{4..5, 7..9}
{5, 7, 9}
{1, 5, 8..9}
{5, 8..9}
{5, 8..9}

Note rows 3, 7, 8, 9!

2	6		3					
5						7		
					1		4	
6			5			2		
		4			8			1
	5		9					
		7						3
					4		1	6

Sudoku

First row, more advanced consistency check:

2
6
{1, 8..9}
3
4
7
{1, 5, 8..9}
{5, 8..9}
{5, 8..9}

alldistinct

2	6		3					
5						7		
					1		4	
6			5			2		
		4			8			1
	5		9					
		7						3
					4		1	6

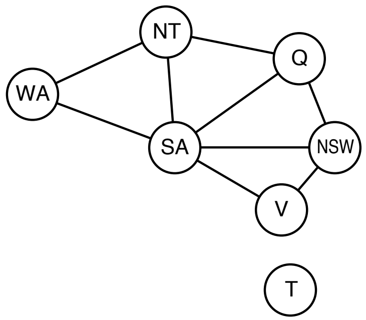
Sudoku

In MiniZinc:

```
include "globals.mzn";

array [1..9,1..9] of var 1..9: v;

predicate row_diff(int: r) =
  all_different ([v[r,c] | c in 1..9]);
predicate col_diff(int: c) =
  all_different ([v[r,c] | r in 1..9]);
predicate subgrid_diff(int: r, int: c) =
  all_different ([v[r+i,c+j] | i,j in 0..2]);

constraint forall (r in 1..9) (row_diff(r));
constraint forall (c in 1..9) (col_diff(c));
constraint forall (r,c in {1,4,7}) (subgrid_diff(r,c));

solve satisfy;

output ["v = ", show(v), "\n"];

v = [
| 2, 6, _, 3, _, _, _, _, _
| 5, _, _, _, _, _, 7, _, _
| _, _, _, _, _, 1, _, 4, _
| 6, _, _, 5, _, _, 2, _, _
| _, _, _, _, _, _, _, _, _
| _, _, 4, _, _, 8, _, _, 1
| _, 5, _, 9, _, _, _, _, _
| _, _, 7, _, _, _, _, _, 3
| _, _, _, _, _, 4, _, 1, 6 |];
```

2	6		3					
5						7		
					1		4	
6			5			2		
		4			8			1
	5		9					
		7						3
					4		1	6

Problem structure



Tasmania and mainland are independent subproblems

Identifiable as connected components of constraint graph

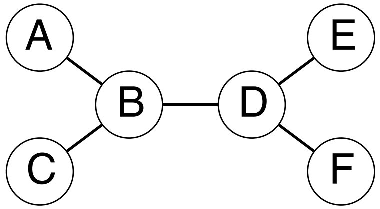
Problem structure contd.

Suppose each subproblem has c variables out of n total

Worst-case solution cost is $n/c \cdot d^c$, **linear** in n

E.g., $n = 80$, $d = 2$, $c = 20$
2^{80} = 4 billion years at 10 million nodes/sec
$4 \cdot 2^{20}$ = 0.4 seconds at 10 million nodes/sec

Tree-structured CSPs



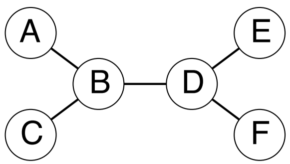
Theorem: if the constraint graph has no loops, the CSP can be solved in $O(n\,d^2)$ time

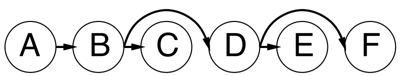
Compare to general CSPs, where worst-case time is $O(d^n)$

This property also applies to logical and probabilistic reasoning:
an important example of the relation between syntactic restrictions
and the complexity of reasoning.

Algorithm for tree-structured CSPs

1. Choose a variable as root, order variables from root to leaves such that every node's parent precedes it in the ordering



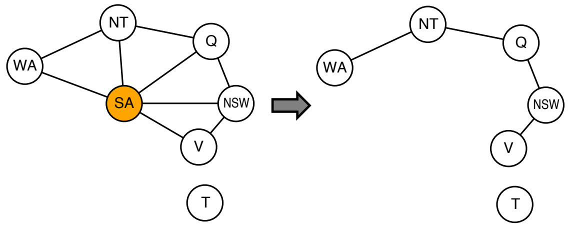


2. For j from n down to 2, apply $\text{RemoveInconsistent}(Parent(X_j), X_j)$

3. For j from 1 to n, assign X_j consistently with $Parent(X_j)$

Nearly tree-structured CSPs

Conditioning: instantiate a variable, prune its neighbors' domains



Cutset conditioning: instantiate (in all ways) a set of variables
such that the remaining constraint graph is a tree

Cutset size c $\Rightarrow$ runtime $O(d^c \cdot (n - c)d^2)$, very fast for small c

Local Search, or Iterative algorithms for CSPs

Hill-climbing, simulated annealing typically work with
"complete" states, i.e., all variables assigned

To apply to CSPs:
  allow states with unsatisfied constraints
  operators **reassign** variable values

Variable selection: randomly select any conflicted variable

Value selection by min-conflicts heuristic:
  choose value that violates the fewest constraints
  i.e., hillclimb with $h(n)$ = total number of violated constraints

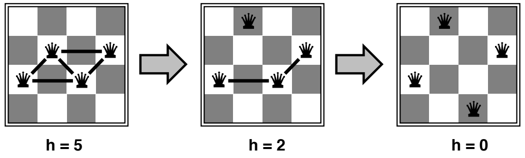
Example: 4-Queens

States: 4 queens in 4 columns ($4^4 = 256$ states)

Operators: move queen in column

Goal test: no attacks

Evaluation: $h(n)$ = number of attacks

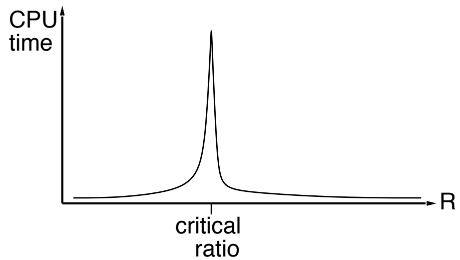


Performance of min-conflicts

Given random initial state, can solve n-queens in almost constant time for arbitrary n with high probability (e.g., n = 10,000,000)

The same appears to be true for any randomly-generated CSP
except in a narrow range of the ratio

$$R = \frac{\text{number of constraints}}{\text{number of variables}}$$



Summary

CSPs are a special kind of problem:
  states defined by values of a fixed set of variables
  goal test defined by constraints on variable values

Backtracking = depth-first search with one variable assigned per node

Variable ordering and value selection heuristics help significantly

Constraint propagation (e.g., arc consistency) does additional work
to constrain values and detect inconsistencies

The CSP representation allows analysis of problem structure

Tree-structured CSPs can be solved in linear time

Iterative min-conflicts is usually effective in practice

But: in the worst case search **will be exponentially complex** anyway!

Programming Assignment 1a

- ♢ Learn how to use MiniZinc (and maybe JaCoP).
  MiniZinc → FlatZinc
  FlatZinc → JaCoP.
- ♢ Practice with sudoku and "send more money".
- ♢ Maybe wait two weeks for the logic lecture.
- ♢ Solve a couple of slightly more interesting problems. Note that focus is actually on modelling, not on just getting the solutions.
- ♢ Attempt to try to solve a complex problem.

`http://www.jacop.eu`, `http://jacop.cs.lth.se`

`http://www.g12.csse.unimelb.edu.au/minizinc/`

`/usr/local/cs/EDAN01/` on `login.student.lth.se`

Thank you

Questions?